Financial Versus Human Resources in the Greek-Turkish Arms Race: A Forecasting Investigation Using Artificial Neural Networks

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Abstract

This paper aims at forecasting the burden on the Greek economy resulting from the arms race against Turkey and at concentrating on the leading determinants of this burden. The military debt and the GDP share of defence expenditure are employed alternatively in order to approximate the measurement of the arms race pressure on Greece, and the method used is that of artificial neural networks. The use of a wide variety of explanatory variables in combination with the promising results derived, suggest that the impact on the Greek economy resulting from this arms race is determined, to a large extent, by demographic factors which strongly favour the Turkish side. Prediction on both miltary debt and defence expenditure exhibited highly satisfactory accuracy, while the estimation of input significance, indicates that variables describing the Turkish side are often dominant over the corresponding Greek ones.

JEL codes: C45, H56

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1. INTRODUCTION

The Greek-Turkish conflict over a variety of strategic issues dates back several centuries, having entangled the two countries to the vicious cycle of a very expensive arms race (Kollias and Makrydakis, 1997). The aim of this paper is to forecast the pressure due to this arms race between Greece and Turkey exercised on the economy of the former. This forecast, established on the basis of the most appropriate explanatory variables, will provide the opportunity to comment on the nature and relative importance of the explanatory variables that determine the burden of this arms race on the Greek economy, as this is approximated by either the military debt of the country or the GDP share of defence expenditure. The method of analysis used is that of Artificial Neural Networks, which, has been considered preferable to the conventional estimation methods for the purposes of the present analysis for reasons analysed later on in this paper.

It is well-known that the cost of an arms race, is the disturbance which excessive military expenditure, and the ensuing budgetary imbalances, bring about to the long-run economic growth of the countries involved, as these strive to maintain the balance of power between one another. The foreign sector of these countries, in particular, to the extent that these are characterised as small, open economies, is considerably burdened since military expenditure is highly import-demanding, crowding out funds intended for alternative, non-military uses, and leading to borrowing abroad in order to finance the military spending programmes. This foreign borrowing exerts an adverse impact on both the domestic and the foreign sector: on the former due to the slow-down of economic growth, as stated earlier, and on the latter because of the burden on the balance of payments, which causes the need for more borrowing, thus creating a vicious cycle of an ever-increasing foreign debt (Stavrinos and Zombanakis, 1998).

The impact of the arms race with Turkey upon the Greek economy has been particularly painful since about 6% to 7% of the country's GDP is annually devoted to military expenditure. The military debt, moreover, has doubled within the decade of the 1990s to reach about 4 billion dollars at the end of 1997, representing roughly 15% of the total external debt of the country. Both these variables reflect the seriousness of the problem for the Greek economy. Research seems to favour the military expenditure rather than the stock of the military debt as an indicator of the pressure exercised upon an economy due to an arms race, with only a few notable exceptions, like McWilliams (1987). A large number of papers have followed Benoit (1978), examining the effects of defence spending on growth, like Deger (1986) and, later on Ward et al. (1991), Buck et. al. (1993), Looney (1994), as well as several authors in Hartley and Sandler (1990).

Concentrating on the impact of an arms race on the the balance of payments and the external debt of the countries that are involved in such a race, the only topic regarding the external sector which appears in the literature concerns the concentration of defence investment on the leading export sectors such as machinery and capital equipment, something which leads to reduction of the availability of exportables and the slowing down of economic growth. Empirical research by Fontanel (1994), considers the independent variables that affect defence expenditure focusing on the impact of military spending in the case of both developed and developing economies, while Levine and Smith (1997), concentrate on the role of military imports in an arms race between two countries. Specific reference to the case of Greece or to the Greek -

Turkish conflict is found in Kollias (1994, 1995 and 1996) and Antonakis (1996 and 1997) who have investigated the economic effects of defence expenditure upon the Greek economy.

The overwhelming majority of papers, employ conventional estimation methods with the notable exeption of Refenes et. al. (1995) who have employed the artificial neural networks approach for determining the defence expenditure of Greece. The advantages of using the neural network facility are multiple and have been repeatedly analysed in the literature (Kuo and Reitsch, 1995; Hill et. al., 1996). The ones that have attracted our attention for the solution of the specific problem are the following. First, the neural networks do not require an a-priori specification of the relationship between the variables involved. This is a major advantage in our case, since there is no such thing as an established theoretical background that describes the behaviour of either the military expenditure or the military debt when these are affected by the independent variables chosen. There does not even seem to be an agreement as to which these variables are. Second, in cases like the present one, in which certain variables are correlated between one another and the pattern of behaviour may be non-linear, the neural networks are more applicable. Finally, studies agree on the superiority of neural networks over conventional statistical methods concerning time-series forecasting.

The main objective of this paper, therefore, as earlier stated, is to forecast the pressure that the arms race between Greece and Turkey exercises on the Greek economy and to indicate, with the help of the artificial neural networks technique, the selection of the most appropriate explanatory variables used in specifying such an “arms-race” function. We shall show, more specifically, that the explanatory variables best describing the behaviour of the authorities and the reasoning behind such decisions are related to a large extent, to the population characteristics of the two countries, being, therefore, of a non-financial nature in its strict sence. Concentrating on such variables seems to be very interesting in the case of the Greek-Turkish conflict, since the comparison in terms of demographic developments is overwhelmingly against Greece.

The description of the technical background is presented in section 3. Section 4 includes the presentation of the explanatory variables used as input in the analysis as well as the various scenaria considered. Section 5 describes the empirical results obtained, comparing them to those drawn on the basis of an OLS estimate. Finally section 6 sums up the conclusions drawn and evaluates the results.

3. TECHNICAL BACKGROUND

3.1 Neural Networks

This section is devoted to describing the emerging technology of artificial neural networks. This technique belongs to a class of data driven approaches, as opposed to model driven approaches. The process of constructing such a "machine", based on available data is addressed by certain general purpose algorithms. The problem is then reduced to the computation of the weights of a feed-forward network to accomplish a desired input-output mapping and can be viewed as a high dimensional, non-linear, system identification problem. In a feed-forward network, the units can be partitioned into layers, with links from each unit in the k^{th} layer being directed to each unit in the $(k+1)^{th}$ layer. Inputs from the environment enter the first layer and outputs from the network are manifested at the last layer. An m-d-1 architecture is shown in Figure 1, which refers to a network with m inputs, d units in the hidden layer and one unit in the output layer.

We use such m-d-1 networks to learn and then predict the behaviour of the time-series. The hidden and output layers realise a non-linear transfer function of the form:

$$f(y) = (1 + \exp(-by))^{-1} \tag{1}$$

$$y = \sum_{i=1}^{n} w_i x_i \tag{2}$$

where x_i*'s* denote the input values of a node, while w_i's the real valued weights of edges incident on a node and n the number of inputs to the node from the previous layer. Equation (1) is known as the sigmoid function where b is the steepness. Also shown in Figure 1 is a special node at the end of the input layer called "bias". This node has a fixed input value of 1 and feeds into all the neurons in the hidden and the output layers, with adjustable weights as the other nodes. Its role is to represent the adjustable neuron threshold levels explicitly in the transfer function input. The nodal representation eliminates the need to treat threshold as a special neuron feature and leads to a more efficient algorithm implementation (Azoff, 1994).

3.2 System Design

From the given time series x={x(t): 1 ≤ t≤ N} we obtain two sets: a training set x_{train}={x(t): 1 ≤ t ≤ T}, and a test set x_{test}={x(t): T < t ≤ N}, where N is the length of the data series. The x_{train} set is used to train the network at a certain level at which convergence is achieved based on some error criterion. This is done by presenting to the network L-times the sequence of inputs and desired outputs (L from now on will be referred to as epochs) and having the learning algorithm to adjust the weights in order to minimize the diversion of the desired value from the predicted one. The network is asked to predict the next value in the time sequence, thus we have one output neuron.

The range of values for the output neuron is limited to [0,1] by the implementation tool used, so the desired values d_i of both the training and the testing sets are normalized to this range just by taking the ratio $di/dmax$, in order to avoid negative values. Then, the output values o_i predicted by the network can be easily restored by taking the inverse transformation $o_{i*} d_{max}$.

The training algorithm used is the well known Error Back Propagation with a momentum term (see e.g. Rumelhart and McLelland, 1986; Azoff, 1994).

3.3 System Implementation, Training and Testing

The system described above has been implemented using a neural network implementation tool, namely the Cortex-Pro Neural Networks Development System (Unistat, 1994). We used several alternative configuration schemes, as regards the number of hidden layers and the nodes within each layer, in order, first to achieve best performance and second, to facilitate comparison between different network architectures. The number of input neurons and the nature of data fed depend on what we call “scenarios”, that is, different cases in which, using some or all of the available input variables/factors, we attempt to forecast the performance of one specific variable not included in the input set. These scenarios will be presented in section 4.

In each scenario, the desired values were normalized in the range [0,1] as stated earlier, while the learning and momentum coefficients (Rumelhart and McLelland, 1986; Azoff, 1994) were kept constant at the positive values of 0.3 and 0.2 respectively.

Every input variable is associated with one neuron in the input layer. Our data series consist of annual observations and the forecasting horizon was set to one step ahead. Determining the number of hidden layers and neurons in each layer can often be a very difficult task and possibly one of the major factors influencing the performance of the network. Too few neurons in a hidden layer may produce bias due to the constraint of the function space which results to poor performance as the network embodies a very small portion of information presented. Too many neurons on the other hand may cause overfitting of data and increase considerably the amount of computational time needed for the network to process data, something which will not necessarily lead to convergence. We therefore have used a variety of numbers of neurons within one hidden layer, while in some cases a two-hidden-layer scheme was also developed in order to investigate whether performance is improved.

The number of iterations (epochs) presenting the whole pattern set during the learning phase is also very important. We have let this number vary during our simulations, since different network topologies, initial conditions and input sets, require different convergence and generalization times. The number of epochs our networks needed for convergence ranged between 3,000 and 10,000. One should be very cautious though when using a large number of epochs, as the network may overfit the data thus failing to generalize.

The problems of bias and data overfitting mentioned above can be overcome by evaluating the performance of each network using a testing set of unseen patterns (testing phase). This set does not participate during the learning process (see e.g. Azoff, 1994). If the network has actually learned the structure of the input series rather than memorizing it then it can perform well when the testing set is presented. Otherwise, if bias or overfitting is really the case, performance will be extremely poor on these “new” data values. Architecture selection is generally based on success during the testing phase, provided that the learning ability was satisfactory.

Performance was evaluated using three different types of errors, specifically the Mean Absolute Error (MAE), the Least Mean Square Error (LMSE) and the Mean Relative Error (MRE). MAE shows the divergence between actual and predicted samples in absolute measures. LMSE is reported in order to have the error condition met by the Back Propagation algorithm. Finally, MRE shows the accuracy of predictions in percentage terms expressing it in a stricter way, since it focuses on the sample being predicted, not depending on the scale in which the data values are expressed or on the units of measurement used. Thus, we are able to estimate prediction error as a fraction of the actual value, this making the MRE the more objective error measure among the three used. LMSE, MAE and MRE are given by the following equations:

$$\mathrm{LMSE} = \frac{1}{2n}\sum_{i=1}^{n}(o_i - d_i)^2 \tag{3}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|o_i - d_i\right| \tag{4}$$

$$\mathrm{MRE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{o_i - d_i}{d_i}\right| \tag{5}$$

where o_i is the actual output of the network, d_i is the desired value when pattern i is presented and n is the total number of patterns.

An important aspect examined in the present analysis is the determination of the significance ordering of the variables involved, that is the selection of the variables which contribute more to the forecasting process. This task can be performed using the notions of input sensitivity analysis, described extensively in Refenes et. al. (1995) and Azoff (1994), based on which one can sum up the absolute values of the weights fanning from each input variable into all nodes in the successive hidden layer, thus estimating the overall connection strength of this variable. The input variables that have the highest connection strength can then be considered as most significant, in the sense of affecting the course of forecasting in a more pronounced way compared to others. Presenting the analytical technical background behind these notions is beyond the scope of this work, since the reader may refer to the sources stated above for further information.

4. INPUT/OUTPUT VARIABLES AND SCENARIOS

The data set used for the multiple simulations includes the 13 variables listed in Table 1, the sources of which are the Bank of Greece, the International Institute of Strategic Studies, the Swedish International Peace Research Centre and the United Nations Population Statistics. Variables A to F and variable Y consist of 36 observations covering the period 1961-1996, while variables G to L consist of 35 observations, up to and including 1995.

Variable Y represents the rate of change of the military debt debt of Greece and shall be used as the dependent variable alternatively to variable C which stands for the Greek GDP share of defence expenditure. The first set of explanatory variables representing the developments in resources characterized as of purely financial nature includes the following: Variable A is the rate of increase of the Greek real GDP, while B represents the aggregate national non-defence investment expenditure, both private and public, again as a percentage of GDP. Variables C and D stand for the GDP shares of defence expenditure in Greece and Turkey respectively, while variables E and F denote GDP shares of non-oil, non-defence imports and defence imports respectively.

The next set of independent variables has been selected to include those that place emphasis on human resources, mostly representing demographic features. Thus G and H stand for defence expenditure per soldier in Greece and Turkey respectively, while I and J denote percentage of armed forces in the population of Greece and Turkey. Finally, K and L indicate the population rate of increase in Greece and Turkey respectively.

Using these variables we formed three scenarios which will be simulated and evaluated:

(i) Financial Resources Scenario, which assumes that the Greek GDP share of defence expenditure or, alternatively, the increase of the stock of military debt is determined by variables representing financial resources of the two countries involved in the arms race as these are described chiefly by national accounts items. The choice of such variables is based on the selection of the variables that seem to perform better in the literature cited earlier on in this paper.

(ii) Human Resources Scenario, which considers the Greek GDP share of defence expenditure or, alternatively, the increase of the stock of military debt as determined by the population characteristics of the two countries involved, rather than the financial resources of the respective sides. Emphasizing on such factors does not seem to be the case, at least as far as we know, in the relevant literature and it is therefore interesting to see the extent to which the population factor may affect the arms race of the countries involved.

(iii) Composite Scenario, created by the combination of those variables in the first two scenarios that have been found to be the most significant using input sensitivity analysis. Table 4 (top four rows) presents a comprehensive summary of the first two scenarios, as regards the specification of input and output variables of a neural network, with each scenario including two alternative cases using either the Greek GDP share of defence expenditure or the rate of change of the stock of military debt as an output variable.

Our primary goals when formulating these scenarios have been, first to determine the predictive ability of neural networks in the context of an arms-race scenario and second to select those explanatory variables that yield the best forecasting performance.

5. EMPIRICAL RESULTS

The training sets of the Financial Resources Scenario consist of 29 annual observations, covering the period 1961-1989 and those of the Human Resources

Scenario of 28, representing the period 1961-1988. The testing sets, in all scenaria, consist of 7 annual samples, referring to the period 1990-1996 for the former scenario, while this period is shorter by one observation, that is 1989-1995, for the latter. The results obtained for each scenario are analyzed in the following section.

5.1 Comparison Between Two Scenarios: Financial vs. Human Resources

Tables 2 and 3 summarize the best results obtained in the context of both scenaria providing for the evaluation of the training as well as the testing phase, in cases in which the arms race pressure is approximated either by the change of the stock of military debt or the GDP share of defence expenditure. It is clear that using the latter as a dependent variable yields much better results in terms of predictive ability of the networks in both scenaria, with all error figures for the testing phase of all networks being slightly superior for the financial resources scenario. The best performance yielded a 93% success against 84% for the human resources scenario in MRE terms. The corresponding network performance when the stock of military debt is used as a dependent variable is rather inferior in terms of all error evaluation figures. In MRE terms the testing phase exhibited 70% and 52% highest prediction success for the financial and human resources scenaria respectively. It is interesting to point out, as a general remark, that when the number of hidden layers and nodes within each layer is increased, providing for a more complex topology, the time needed for the network to converge, as this is expressed in terms of number of epochs, is reduced to approximately half the training time of the simple architectures.

Figure 2 presents graphically the course of forecasting of stock of military debt in (a) and the GDP share of defence expenditure in (b), for the financial scenario that yielded the best predictive performance. As stated earlier, based on the error measures, the latter appears to have higher predictive ability compared to the former. The two variables apparently have different variances, thus we have calculated the correlation coefficient between actual and predicted samples in order to eliminate the possibility the results are numerical artifacts. Indeed this enhanced our results, as the correlation coefficient for the training phase was 0.86 for the debt case and 0.98 for the expenditure one, while for the testing phase 0.80 for the former and 0.87 for the latter.

5.2 Estimation of Input Significance

The input significance ordering is a procedure most interesting for the purposes of the present paper, since it serves a twin purpose. First, it involves determining the most significant input variables in terms of explanatory power in the two scenarios considered thus far. This hierarchy ordering is based on the forecasting performance of these variables on both the rate of change of the stock of military debt and the Greek GDP share of defence expenditure, and leads to building the composite scenario. Second, the selection of the most significant variables is expected to lead to interesting conclusions concerning their nature and their role in determining the pressure of the arms race on the Greek economy.

From the technical point of view, the input significance ordering has been arranged by summing up the absolute values of the weights of the wires connecting an input variable to every node in the next layer. After this procedure was performed for all input variables, the weights were ranked in descending order. This process was repeated for every network topology for comparison purposes. The results presented in Table 4 are summarized in the following subsection, the letter w denoting the weight of the variable, which appears as a subscript.

5.2.1 Financial Resources Results:

Debt Case

The ranking showed that all networks, regardless the number of nodes or hidden layers, exhibited the same significance order: $w_D>w_C>w_F$, with the remaining variables having very low strengths. It is interesting to see, therefore, that the Turkish GDP share of military expenditure is the leading determinant of the Greek external military debt, its weight being by far the largest, almost double that of each of the rest two, the weights of which are almost equal. This finding supports the view in favour of the existence of an arms race between the two rival countries and underlines the pressure that this arms race exercises on the Greek economy. The second variable in terms of significance is the Greek GDP share of defence expenditure, while the Greek import bill on military equipment comes third in significance ordering.

Expenditure Case

The determination of the significant input variables according to their weights summation, provided the same ordering for all networks: $w_F>w_Y>w_D$. This result has been, to a large extent, expected. The selection of the determinants is essentially the same as in the previous case, with only the ordering being reversed. It is, therefore, the expenditure on military imports that plays the dominant role in determining the Greek GDP share of defence spending, a dominance being by far the most pronounced compared to the rest two explanatory variables, (i.e. the change of the Greek military external debt and the Turkish GDP share of defence spending, as indicated by the comparison of the relevant weights). This rearrangement of the order of significance, in this case, reinforces the conclusions already derived in the debt case. The pressure exercised from the part of the Turkish side is always dominant expressed by the presence of this country's GDP share of defence expenditure as one of the leading determinants of the Greek corresponding share. The importance of the military debt as the second leading variable determining the Greek defence spending simply shows a reversal of roles in terms of causality direction between the two variables with reference to the case of military debt determination and supports earlier work on the topic examining the vicious cycle between defence expenditure and military debt (Stavrinos and Zombanakis, 1998).

5.2.2. Human Resources Results

Debt Case

Determining the military debt along the lines of the Human Resources scenario indicates that the Greek defence expenditure per soldier, the rate of increase of the Greek population and the proportion of armed forces in the population of Turkey are the leading explanatory variables in that order ($w_G>w_K>w_J$). The weights of the first two independent variables are almost equal, something that does not allow for a clear-cut determination of the ordering of importance between them. Again, however, a variable representing the resources of the "other side" is strongly present among the leading determinants of the Greek external military debt, only to support, once more, the existence of an arms race environment .

Expenditure Case

This case is unique in the sense that it is the only one in which variables describing the Turkish side are not among the leading determinants of the pressure on the Greek economy due to this arms race. The weight ranking resulted the order $w_G>w_I>w_K$. Thus, the Greek GDP share of military expenditure is determined chiefly by the Greek defence spending per soldier, which this time, appears to be the leading determinant by far, to be followed by the proportion of armed forces in the Greek population and the rate of increase of the population in the country.

5.3 Composite Scenario

The preceeding Input Significance Analysis leads us to making the main point of the present paper in terms of what we refer to as “the Composite Scenario”. This involves combining the three most significant inputs of each of the two scenarios earlier examined, namely the Financial Resources and the Human Resources ones. These input variables have been selected on the basis of the input sensitivity ordering indicated in Table 4 (top four rows). The training and testing sets of this scenario have the same data length as those in the Human Resources Scenario.

5.3.1. Results

Debt Case

Various network topologies have been developed in the context of the Composite Scenario trained using C, D, F, G, J and K as input variables and over a variety of iterations numbers. Table 5 (top half) summarizes the best results obtained when foracasting the Y variable and provides for an evaluation of both the training and testing phase in the case in which the burden of the arms race for the Greek economy is approximated by the military debt.

The interesting result in this scenario has to do with both the nature of the variables selected as well as their explanatory power. We see that the network performance is almost equally successful compared with the best results obtained in cases of debt determination in the previous two scenarios. In fact the errors derived in the testing phase are very close to those in the corresponding case of the Financial Resources

Scenario and considerably lower compared to the errors of the debt-determination case of the Human Resources Scenario. Thus, the MREs indicated a roughly 70% prediction success for the 6-8-4-1 topology that performed best, denoting that the new set of input variables performs as successfully as it did in the case of the Financial Resources Scenario in forecasting the military external debt.

Expenditure Case

The final simulation employs variables Y, D, F, G, I and K, found to be more significant by input sensitivity analysis, to forecast variable C, the GDP share of defence expenditures in Greece. The results obtained here and summarized in Table 5 (bottom half), being similar to those in the previous case.

All networks provided for a very satisfactory performance, the testing phase errors being very close to those in the corresponding case of the Financial Resources scenario. The best topology is the 6-8-1 architecture with a prediction success of approximately 88% (MRE terms).

5.3.2 Estimation of Input Significance

The Input Significance exercise has been performed on the basis of the results obtained in the case of the Composite scenario along the lines of section 5.2. Its findings are summarized in Table 4 (bottom two rows) and they seem to be very interesting since they provide a full picture as to whether and the extent to which human resources may account for the development of the military debt or the Greek share of GDP expenditure, thus illustrating a number of very important points.

Debt Case

As regards the question of determining the military external debt of Greece, the rate of the Greek population increase, a Human Resources indicator, seems to be almost twice more powerful compared to the other explanatory variables, the explanatory power measured by the relevant weight computed. Equally interesting is the fact that the second in order of importance determinant is another Human Resources indicator, this time, however, concerning the “opposite side”, the proportion of the armed forces in the population of Turkey. Finally, the Greek military expenditure per soldier comes third in terms of explanatory power in this case. It is worth noting, finally, that the top three determinants in this case are the same as the top three ones in the corresponding Human Resources case, but in a different order.

Expenditure Case

In the case in which the Greek GDP share of defence spending is taken to approximate the arms-race pressure on the Greek economy, the Greek defence expenditure per soldier is now the leading explanatory variable. The proportion of armed forces in the Greek population comes second in explanatory power, while the GDP share of military expenditure in Turkey is third in importance. It is interesting to see, therefore, that the first two independent variables are derived from the Human Resources Scenario while the third one that is not, represents the “Other side”, underlining once more the dominant influence of the Turkish side on the defence burden of Greece.

5.4 Ordinary Least Squares Regression

Concluding this analysis, we thought that it would be interesting to investigate the extent to which our neural network topologies are suitable for forecasting the arms-race pressure on the Greek economy better than a conventional OLS exercise, using the same explanatory variables.

We tried OLS regressions with the dependent variable being the rate of change of the military external debt and, alternatively, the Greek GDP share of defence expenditure, for all three scenarios used. All series have been found to be stationary in their first differences, on the basis of the ADF test. Due to the small number of available observations, the OLS has been performed using the entire sample period, (i.e. 1961-1996, while the forecasting period involves the last seven years, the forecasting period of the corresponding neural networks exercise). The estimation results for all equations are presented in Table 6, with t-values indicated in parentheses and the variable *res* denoting the residuals of the corresponding long-run estimates. The results are satisfactory, bearing the expected signs. The ambiguity of the sign concerning the rate of the Greek population increase is expected. One may argue that a high rate of population growth will lead to increasing manpower in most units and therefore, the requirements for more equipment. An opposing view, however, appears to interpret recent developments in the Greek armed forces in a different way: The demands of modern warfare call for small, flexible units, very well trained and equipped with high technology weapons. In face of the slowing down of the Greek population growth this calls for a heavier arms race burden in order to finance this shift to the modernisation of the armed forces of the country. To the extent that one may comment on the hierarchy ordering of the leading determinants taking the t-statistic as a measure, it seems that in the debt case, the OLS ordering coincides with that of the neural networks in the qualification of two out of three major determinants, namely the Greek defence expenditure per soldier and the percentage of Greek population increase. In the expenditure case, the ordering indicated by the OLS exercise shows a remarkable coincidence to that given by the neural networks, since they both agree on the qualification of the top three explanatory variables in the same order of importance.

The results of the forecasts using the OLS regressions are shown in Table 7. Forecasting performance does not exceed the accuracy of 65% for the debt case and 45% for the expenditures case (testing phases) based on MRE terms, suggesting that almost all neural networks topologies performed better than the OLS.

6. CONCLUSIONS

The arms race which has been going on between Greece and Turkey for a long period of time, has become the cause of a considerable pressure on the economies of the two countries. This paper has demonstrated that, apart from the financial aspect of the problem, there is another dimension, that of the human resources, which is at least equally important to the financial resources aspect in determining the arms race load imposed on the Greek economy. The demographic developments in the two countries, to be more specific, have been proven to exercise significant explanatory power, affecting the decisions of the Greek authorities on adding to the already heavy burden of the arms race on the economy of Greece. This analysis has thus led to deriving certain interesting conclusions:

1. The neural networks methodology employed has attained a very satisfactory prediction level for the arms race pressure imposed on the Greek Economy, as this is proxied by both the change of the miltary debt and the GDP share of defence

expenditure. This prediction performance is superior to that attained using corresponding OLS estimations in all cases.

2. In the context of the so-called “composite scenario”, in which both financial and human resources variables have been included, the latter are dominant over the former in determining and forecasting the burden of an arms race on the Greek Economy, as this is approximated by either the military debt or the GDP share of defence spending.
3. In all scenaria and cases tried, variables representing or approximating the Turkish side are among the dominant ones in determining the pressure due to this arms race on the Greek economy. The input sensitivity analysis proves that one of the top three variables determining this pressure represents the “opposite side” in all cases, either in financial resources terms (GDP share of defence spending) or in human resources terms (proportion of armed forces in the population). The former is indeed one of the top determinants in terms of sensitivity in almost all scenaria. This finding verifies and underlines the fact that the pressure excercised on the Greek economy by this arms race will be very difficult to mitigate since it is to a considerable extent exogenous, depending on the policy followed by the “opposite side”.
4. Combining the above two conclusions leads to suggesting that in the context of the Greek - Turkish arms race, the human resources factor deserves more attention than what it has been given in the literature thus far. Demographic developments in the two countries, provide for a serious disadvantage for the Greek side, since its population, unlike that of Turkey, is aging, increasing at very low rates, which, on certain occasions, have even turned negative during the recent past. These developments, combined with pronounced differences as regards the standard of living between the two countries have made the need for expansion of what is

termed “vital space”, more than demanding for the Turkish side. The Greek side, in its turn, aiming at facing this dynamism from the part of its neighbour, and bearing in mind its disadvantages as regards human resources developments, has turned to improving the efficiency of its armed forces, placing emphasis on their flexibility and speed of reaction, as well as on the quality of the equipment and technology used. This policy, in its turn, demands either buying the latest version of equipment or upgrading the quality and efficiency of items already in use. The so-called “purchase of the century”, involving placing an order for a large number of highly qualified military aircraft during the mid - eighties has been just the beginning of a series of structural reform measures towards this direction. The problem in this case, as earlier stated, is that Greece, facing a binding and prohibitive domestic supply constraint concerning its defence industry, is compelled to resort to importing expensive, high - technology equipment, thus increasing, not only its defence expenditure but also its debt burden. It seems therefore interesting to suggest that future research should be directed towards the trade - off between capital and human resources as an additional determinant affecting the future course of the Greek - Turkish arms race.

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TABLES

Table 1 : *Variables, Data and Sources* [*]**.**

Code	Data Series	Source
A	Rate of change of Greek GDP.	Greek National Accounts

B	National investment of Greece as a percentage of GDP.	Greek National Accounts
C	Military expenditure of Greece as a percentage of GDP.	NATO, SIPRI (Swedish International Peace Research Institute)
D	Military expenditure of Turkey as a percentage of GDP.	NATO, SIPRI
E	Non-oil civilian imports of Greece as a percentage of GDP.	Bank of Greece
F	Non-oil military imports of Greece as a percentage of GDP.	Bank of Greece
G	Greek defence expenditure per soldier (constant 1995 prices).	IISS (International Institute of Strategic Studies-London)
H	Turkish defence expenditure per soldier (constant 1995 prices).	IISS
I	Greek armed forces per 1000 people.	IISS
J	Turkish armed forces per 1000 people.	IISS
K	Percentage of the Greek population increase.	U.N. Population Statistics
L	Percentage of the Turkish population increase.	U.N. Population Statistics
Y	Rate of change of the Greek military debt.	Bank of Greece

*Data series are available upon request

Table 2: ***Prediction Results: Financial Resources Scenario, Debt and Expenditure Cases (standard errors in parentheses).***

		Training Phase			Testing Phase		
Network*	**Epochs**	**MAE**	**LMSE**	**MRE**	**MAE**	**LMSE**	**MRE**
			Debt Case				
		Inputs: A, B, C, D, E, F			Output: Y		
6-4-1	10,000	0.05842 (0.0114)	0.00347 (0.0015)	0.091 (0.0191)	0.20003 (0.0487)	0.02710 (0.0106)	0.295 (0.0811)
6-8-1	10,000	0.04259 (0.0102)	0.00212 (0.0014)	0.064 (0.0101)	0.30147 (0.0761)	0.05593 (0.0166)	0.301 (0.0822)
6-8-4-1	5,000	0.05337 (0.0109)	0.00311 (0.0015)	0.080 (0.0145)	0.2301 (0.0585)	0.0368 (0.0146)	0.318 (0.0854)
6-32-16-1	6,000	0.06979 (0.0071)	0.00533 (0.0004)	0.098 (0.0121)	0.18330 (0.0281)	0.02329 (0.0041)	0.288 (0.0400)
			Expenditure Case				
		Inputs: A, B, Y, D, E, F			Output: C		
6-4-1	5,000	0.04334 (0.0064)	0.00148 (0.0040)	0.059 (0.0110)	0.09570 (0.0215)	0.00596 (0.0022)	0.124 (0.0279)
6-8-1	3,000	0.03130 (0.0048)	0.00080 (0.0003)	0.031 (0.0061)	0.05413 (0.0052)	0.00248 (0.0009)	0.087 (0.0065)
6-8-4-1	3,000	0.0579 (0.0115)	0.00350 (0.0018)	0.085 (0.0200)	0.06061 (0.0196)	0.00311 (0.0020)	0.089 (0.0196)

* "m-d-n" stands for m input nodes, d nodes in the hidden layer and n output nodes. "m-d-p-n" stands for m input nodes, d nodes in the first hidden layer, p nodes in the second hidden layer and n output nodes.

Table 3: ***Prediction Results: Human Resources Scenario, Debt and Expenditure Cases (standard errors in parentheses).***

		Training Phase			Testing Phase		
Network*	**Epochs**	**MAE**	**LMSE**	**MRE**	**MAE**	**LMSE**	**MRE**
Debt Case							
Inputs: G, H, I, J, K, L					Output: Y		
6-4-1	10.000	0.04548 (0.0097)	0.00236 (0.00090)	0.060 (0.0143)	0.20985 (0.0654)	0.03483 (0.0133)	0.537 (0.2068)
6-8-1	8.000	0.04411 (0.0088)	0.00226 (0.00070)	0.058 (0.0125)	0.30073 (0.0537)	0.05386 (0.0187)	0.610 (0.0901)
6-8-4-1	5.000	0.04303 (0.0093)	0.00218 (0.00080)	0.056 (0.0132)	0.20729 (0.0383)	0.02587 (0.0092)	0.487 (0.1298)
6-32-16-1	8.000	0.01414 (0.0023)	0.00021 (0.00005)	0.017 (0.0038)	0.31205 (0.0714)	0.06403 (0.0231)	0.657 (0.0728)
Expenditure Case							
Inputs: G, H, I, J, K, L					Output: C		
6-4-1	5,000	0.03660 (0.0035)	0.00083 (0.00010)	0.049 (0.0049)	0.16086 (0.0091)	0.01318 (0.0013)	0.205 (0.0135)
6-8-1	3,000	0.02100 (0.0029)	0.00034 (0.00008)	0.027 (0.0047)	0.12362 (0.0166)	0.00846 (0.0022)	0.159 (0.0226)
6-8-4-1	3,000	0.03816 (0.0035)	0.00089 (0.00012)	0.051 (0.0049)	0.16227 (0.0091)	0.01341 (0.0014)	0.207 (0.0135)

* "m-d-n" stands for m input nodes, d nodes in the hidden layer and n output nodes. "m-d-p-n" stands for m input nodes, d nodes in the first hidden layer, p nodes in the second hidden layer and n output nodes.

Table 4: ***Leading Determinants for Each Scenario, Based on Input Sensitivity Analysis.***

Scenario	Case Study	Leading Determinants*	Output
Financial Resources	Debt	$W_D > W_C > W_F$	Y
	Expenditure	$W_F > W_Y > W_D$	C
Human Resources	Debt	$W_G > W_K > W_J$	Y
	Expenditure	$W_G > W_I > W_K$	C
Composite Resources	Debt	$W_K > W_J > W_G$	Y
	Expenditure	$W_G > W_I > W_D$	C

*W_N denotes the sum of the absolute values of the weights of the N_{th} input variable node connections.

Table 5: ***Prediction Results: Composite Scenario, Debt and Expenditure Cases (standard errors in parentheses).***

		Training Phase			Testing Phase		
Network*	**Epochs**	**MAE**	**LMSE**	**MRE**	**MAE**	**LMSE**	**MRE**
Debt Case							
	Inputs:	C, D, F, G, J, K			Output:	Y	
6-4-1	10.000	0.04074	0.00290	0.058	0.19735	0.03006	0.539
		(0.0120)	(0.0016)	(0.0154)	(0.0594)	(0.0136)	(0.2228)
6-8-1	10.000	0.02262	0.00059	0.033	0.25300	0.04335	0.496
		(0.0044)	(0.0002)	(0.0065)	(0.0615)	(0.0183)	(0.0932)
6-8-4-1	5.000	0.02221	0.00052	0.029	0.15384	0.01589	0.306
		(0.0043)	(0.0001)	(0.0066)	(0.0368)	(0.0060)	(0.0755)
6-32-16-1	6.000	0.02086	0.00047	0.031	0.17177	0.02163	0.328
		(0.0040)	(0.0001)	(0.0067)	(0.0479)	(0.0099)	(0.0820)
Expenditure Case							
	Inputs:	Y, D, F, G, I, K			Output:	C	
6-4-1	5,000	0.03014	0.00066	0.040	0.14329	0.01131	0.182
		(0.0039)	(0.0001)	(0.0051)	(0.0187)	(0.0022)	(0.0258)
6-8-1	3,000	0.02350	0.00043	0.033	0.09336	0.00518	0.119
		(0.0033)	(0.0001)	(0.0050)	(0.0166)	(0.0013)	(0.0222)
6-8-4-1	3,000	0.02605	0.00048	0.037	0.09964	0.00592	0.127
		(0.0029)	(0.0001)	(0.0045)	(0.0179)	(0.0015)	(0.0239)

* "m-d-n" stands for m input nodes, d nodes in the hidden layer and n output nodes. "m-d-p-n" stands for m input nodes, d nodes in the first hidden layer, p nodes in the second hidden layer and n output nodes.

Table 6: ***OLS Regression Results on Military Debt and Defence Expenditure (t-values in parentheses).***

Financial Resources Scenario			Human Resources Scenario			Composite Scenario		
Varia-bles	**Debt**	**Expen-diture**	**Varia-bles**	**Debt**	**Expen-diture**	**Varia-bles**	**Debt**	**Expen-diture**
Constant	-0.04 (-0.76)	0.00 (0.00)	**Constant**	-0.02 (-0.29)	0.01 (0.16)	**Constant**	-0.01 (-0.10)	0.01 (0.10)
A	0.44 (0.47)	4.39 (4.82)	**G**	0.05 (2.90)	0.15 (5.07)	**D**	0.07 (0.84)	0.22 (1.85)
B	-3.09 (-1.21)	-4.99 (-1.90)	**H**	0.13 (2.03)	0.10 (1.02)	**F**	0.47 (3.05)	0.09 (0.38)
C	0.11 (1.53)	———	**I**	0.14 (2.46)	0.42 (3.36)	**Y**	———	0.12 (0.72)
D	0.09 (1.20)	0.26 (2.94)	**J**	0.10 (2.26)	0.18 (2.10)	**G**	0.05 (2.78)	0.12 (4.51)
E	7.88 (2.80)	0.34 (0.13)	**K**	-0.13 (-3.12)	0.19 (2.61)	**K**	-0.09 (-2.47)	0.10 (1.77)
F	0.30 (1.91)	0.21 (1.30)	**L**	0.07 (1.83)	0.15 (1.98)	**I**	——	0.19 (2.58)
Y	———	0.21 (1.69)	———	———	———	**J**	0.10 (2.07)	———
———	———	———	———	———	———	**C**	0.03 (0.52)	———
***res*(-1)**	-1.39 (-7.22)	-1.27 (-10.22)	***res*(-1)**	-1.35 (-5.93)	-0.94 (-4.24)	***res*(-1)**	-1.27 (-7.12)	-1.23 (-6.31)
R^2	0.78	0.90	**R^2**	0.76	0.75	**R^2**	0.81	0.81
D.W.	1.97	1.55	**D.W.**	2.14	2.04	**D.W.**	2.40	1.88

Table 7: ***Ordinary Least Squares Prediction Errors***

		Overall Period			Period of testing*		
Scenario	**Case**	**MAE**	**LMSE**	**MRE**	**MAE**	**LMSE**	**MRE**
Financial Resources	Debt	0.154	0.024	0.912	0.221	0.046	0.409
	Expenditure	0.223	0.031	0.862	0.219	0.037	0.629
Human Resources	Debt	0.165	0.032	0.923	0.175	0.035	0.363
	Expenditure	0.287	0.096	0.727	0.318	0.099	0.862
Composite	Debt	0.152	0.023	0.749	0.192	0.031	0.806
	Expenditure	0.228	0.066	0.521	0.241	0.067	0.543

* This period corresponds to the one used as a testing phase for the neural networks.